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Plant Leaf Disease Detection Using Deep Learning

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ABSTRACT :

In order to improve food security through precise disease diagnosis, the study investigates the use of deep learning, more especially Convolutional Neural Networks (CNNs), for the identification of plant leaf diseases in smart farming. CNNs are recognised as a key tool for camera-assisted disease diagnosis because of their capacity to capture colours and textures unique to a certain disease. The study highlights how useful and afford- able leaf photos are in the developing field of plant phenomics. CNNs are known for their better performance, but their broader use is limited by the acknowledged difficulty of restricted dataset representation. The suggested method, called "PiTLiD," combines transfer learning with an Inception-V3 convolutional neural network that has already been trained in order to get around this drawback. PiTLiD uses phenotypic data to identify plant leaf diseases from limited datasets. Experiments conducted on a range of datasets with small sample sizes show that PiTLiD performs better than current methods. By using a deep learning- based method to diagnose plant diseases, this study advances the science of plant phenomics by providing a useful tool for identifying plant disorders.

Index Terms—Deep learning, CNN, Plant phenomics,Plant Disease Dignosis,Data Preprocessing,Feature Extraction.

INTRODUCTION:

In the realm of agriculture, our research focuses on achiev- ing four key objectives. Firstly, we aim to develop a robust system for detecting plant leaf diseases, providing invaluable support to farmers. Secondly, we strive to enhance crop monitoring and management, empowering farmers to make informed decisions. Thirdly, we work to improve the accuracy of existing deep learning-based methods in disease identifica- tion, minimizing errors. Lastly, by maintaining crop quality, we ultimately contribute to the vital goal of food production. Our scope encompasses multiclass classification of plant leaf diseases, early disease detection, and increased crop yield pro- duction. However, there are constraints to address. Variations in lighting and background pose challenges, calling for robust algorithms. Overlapping symptoms among diseases require innovative classification techniques. Furthermore, given the dynamic nature of plant diseases, regular updates are necessary to incorporate new disease types. In con clusion, this research seeks to revolutionize disease detection and crop management, bolstering the agricultural industry and global food production In the realm of agriculture, our research focuses on achieving four key objectives. Firstly, we aim to develop a robust system for detecting plant leaf diseases, providing invaluable support to farmers. Secondly, we strive to enhance crop monitoring and management, empowering farmers to make informed decisions. Thirdly, we work to improve the accuracy of ex- isting deep learning-based methods in disease identification, minimizing errors. Lastly, by maintaining crop quality, we ultimately contribute to the vital goal of food production. Our scope encompasses multiclass classification of plant leaf diseases, early disease detection, and increased crop yield pro- duction. However, there are constraints to address. Variations in lighting and background pose challenges, calling for robust algorithms. Overlapping symptoms among diseases require innovative classification techniques. Furthermore, given the dynamic nature of plant diseases, regular updates are necessary to incorporate new disease types. In conclusion, this research seeks to revolutionize disease detection and crop management, bolstering the agricultural industry and global food production CNNs are a class of deep neural networks well-suited for processing visual data due to their ability to automatically learn hierarchical features from raw pixel values. Leveraging the architectural advancements of CNNs, our objective is to construct a highly effective model capable of accurately identifying and categorizing objects within images. By delving into the intricacies of CNN architecture and incorporating transfer learning techniques, we seek to optimize the model's performance and generalization capabilities. Through rigorous experimentation and validation, we anticipate surpassing tradi- tional machine learning approaches, delivering a versatile and scalable solution poised to make significant strides in various domains. This project underscores the transformative potential

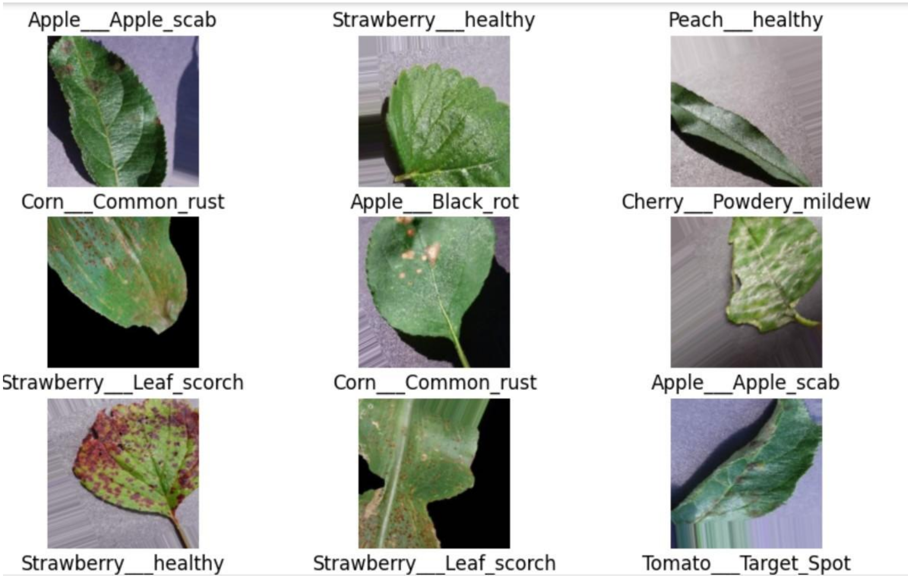

Fig. 1. Diseased leaf with labels

of CNNs in revolutionizing image classification tasks, paving the way for enhanced decision-making systems and intelligent applications in today's data-driven world.

LITERATURE REVIEW

U. Barman et al. tackled potato disease classification with an unbalanced dataset of approximately 1000 images per class: early blight, late blight, and healthy potatoes. They balanced the dataset using data augmentation techniques. Employing a custom CNN model tailored for image classification and comparing it with a fine-tuned MobileNet V2 model, they sought optimal performance. Emphasizing data quality, they implemented preprocessing methods such as grayscale scaling, Gaussian blur subtraction, and noise filtering to enhance train- ing data quality. Their approach highlighted the importance of addressing class imbalance for robust classification in agricul- tural disease monitoring. Through meticulous data preprocess- ing and model selection, they illuminated new pathways for advancing potato disease classification, underscoring machine learning's transformative potential in agricultural research The custom CNN architecture was meticulously designed to leverage the unique characteristics of potato disease images, aiming to maximize classification accuracy and reliability. By conducting a comprehensive comparative analysis against the MobileNet V2 model, renowned for its efficiency in image recognition, the researchers provided valuable insights into the effectiveness of different model architectures for this task. Additionally, their study emphasized the critical role of data augmentation techniques in addressing class imbalance, thereby ensuring that the models were trained on a repre- sentative and diverse set of samples. The implementation of preprocessing methods such as grayscale scaling, Gaussian blur subtraction, and noise filtering further refined the training data, facilitating more nuanced feature extraction during model training. Through their pioneering work, U. Barman et al. not only deepened our understanding of agricultural disease monitoring but also highlighted the transformative potential of machine learning in addressing complex real-world challenges in agriculture.[1].

In this comparative study, the efficacy of three deep learning models - Convolutional Neural Network (CNN), VGG16, and

VGG19 - was investigated for the detection of plant diseases. Utilizing a dataset comprising 9,127 annotated plant images, performance metrics including accuracy, F1 score, recall, and precision were employed for comprehensive evaluation. The CNN model exhibited superior performance, achieving the highest accuracy (0.97) and F1 score (0.95), showcasing its efficacy in disease detection tasks. Notably, VGG16 and VGG19 also demonstrated commendable performance with accuracies of 0.96 and 0.95, respectively, highlighting their potential utility in similar applications.

The utilization of deep learning methodologies offers sig- nificant advantages such as automated feature extraction and scalability, enhancing the efficiency and scalability of disease detection systems. However, these approaches are not without limitations, including susceptibility to overfitting, resource- intensive training requirements, and challenges related to data quality and annotation.

The findings underscore the need for further research to ex- plore the robustness and generalizability of these models under diverse environmental and operational conditions. Addressing challenges such as overfitting and resource constraints will be crucial to realizing the full potential of deep learning in agricultural disease monitoring applications.

In conclusion, this comparative analysis provides valuable insights into the performance of various deep learning models for image classification tasks, with implications extending beyond the realm of agriculture to diverse sectors including healthcare, environmental monitoring, and industrial quality control.[2].

This study addresses the pervasive issue of crop losses due to plant diseases worldwide by introducing a mobile application empowered by deep learning object detection. The application harnesses the power of the Faster R-CNN object detector, incorporating an Inception-v2 backbone network to ensure robust and efficient disease detection capabilities.

Experiments conducted on grape disease images showcase the remarkable efficacy of the mobile application, achieving an impressive accuracy of 97.9

The potential impact of this mobile application is profound, particularly for farmers and crop growers lacking expertise in plant disease identification. By enabling early disease de- tection and control measures, the application holds promise in mitigating crop losses and curbing the spread of diseases within agricultural settings.

This innovative solution not only empowers farmers with timely and accurate disease diagnosis but also streamlines the decision-making process, facilitating prompt intervention strategies. Moreover, the accessibility of the application di- rectly on smartphones enhances its usability and practicality, reaching even remote agricultural communities with limited resources.

By leveraging cutting-edge technology in a user-friendly interface, the mobile application represents a significant step towards sustainable agriculture practices. Its deployment has the potential to revolutionize disease management strategies,

fostering resilience in agricultural systems and contributing to global food security efforts. [3].

The emergence of plant phenomics has revolutionized the identification of plant diseases by offering a cost-effective and efficient approach utilizing leaf images. Among the various methodologies employed for plant disease identification, con- volutional neural networks (CNNs) have garnered widespread popularity due to their exceptional performance. However, CNNs encounter a significant challenge when confronted with small datasets, which hampers their widespread adoption.

Addressing this limitation, this study proposes a novel method termed PiTLiD (Plant Leaf Disease Identification) that harnesses the power of pretrained Inception-V3 CNNs and transfer learning. By leveraging phenotype data from plant leaves with limited sample sizes, PiTLiD aims to overcome the constraints posed by small datasets in disease identification tasks.

To evaluate the efficacy and robustness of the proposed method, comprehensive experiments were conducted across several datasets characterized by limited samples. The results demonstrate that PiTLiD surpasses other comparative methods in terms of accuracy and performance metrics, showcasing its superiority in plant disease identification tasks with small sample sizes.

This research marks a significant advancement in the field of plant phenomics by introducing a tailored plant disease identification tool based on deep learning algorithms. By effectively leveraging transfer learning and pretrained CNN architectures, PiTLiD offers a promising solution to the chal- lenges associated with small datasets, thereby enhancing the efficiency and accuracy of disease diagnosis in agricultural settings. The implementation of PiTLiD has the potential to revolutionize plant disease management practices, contribut- ing to improved crop yields, reduced losses, and sustainable agriculture initiatives. [4].

Plant diseases pose a significant threat to agricultural pro- duction, impacting both the quality and quantity of crops. As plant structures and cultivation practices evolve, the emergence of new diseases on plant leaves continues to challenge agricul- tural sustainability. Therefore, accurate classification and early detection of plant leaf diseases are imperative to mitigate the spread of infections and support healthy plant growth.

This study presents a novel lightweight deep convolutional neural network (CNN) model specifically designed to extract high-level hidden features from plant leaf images. These deep features are complemented by traditional handcrafted local binary pattern (LBP) features, enabling the capture of local texture information essential for disease identification.

The performance of the proposed model is thoroughly evaluated on three publicly available datasets, namely Apple Leaf, Tomato Leaf, and Grape Leaf. Remarkably, the proposed approach achieves exceptional validation and test accuracies across these datasets, ranging from 96.5% to 99% for valida- tion and 96.5% to 98.8% for test accuracy.

The research focused on leveraging deep learning models to detect and recognize plant diseases, utilizing a dataset compris-

ing 35,000 images of healthy plant leaves and leaves infected with diseases. The trained system demonstrated remarkable accuracy, achieving an impressive rate of 96.5% in detecting plant diseases and identifying disease-free plants. Notably, the model showcased 100% accuracy in recognizing both the plant variety and the specific type of disease affecting the plant, underscoring its potential as an effective tool for plant disease detection and diagnosis.

The proposed model in this study employed two pre- trained convolutional neural networks (CNNs), EfficientNetB0 and DenseNet121, to extract deep features from images of corn plants. Comparative analysis with other pre-trained CNN models, ResNet152 and InceptionV3, revealed superior per- formance, with the proposed model achieving a classification accuracy of 98.56%. This outperformed ResNet152 and In- ceptionV3, which attained accuracies of 98.37% and 96.26%, respectively.

The architecture of the proposed CNN model comprised two branches, each featuring a preprocessing function, a feature extractor, average pooling, and a fully connected layer. These design elements collectively contributed to the model's robust performance and high accuracy in classifying plant diseases, demonstrating its potential utility as an advanced tool for agricultural disease management and crop protection. [5].

The research utilized a dataset containing 35,000 images depicting healthy plant leaves alongside leaves afflicted with diseases. Employing deep learning models, the researchers trained the system to discern and categorize plant diseases while also identifying disease-free plants. The trained model exhibited exceptional performance, boasting an accuracy rate of 96.5%. Remarkably, it showcased a perfect accuracy of 100% in recognizing both the plant variety and the specific disease type afflicting the plant. This underscores the system's potential as an immensely effective tool for detecting and diagnosing plant diseases. Such capabilities hold profound implications for enhancing agricultural productivity and safe- guarding crop health. By leveraging advanced deep learning techniques, the research contributes to the development of innovative solutions aimed at addressing critical challenges in plant disease management. Furthermore, the findings offer valuable insights into the application of artificial intelligence in agriculture, paving the way for the implementation of au- tomated systems capable of rapidly and accurately diagnosing plant health issues. Ultimately, the research serves to advance our understanding of plant pathology and lays the groundwork for the deployment of cutting-edge technologies to ensure global food security and sustainable agricultural practices.[6]. In this study, a novel approach is proposed for plant disease classification, leveraging two pre-trained convolutional neural networks (CNNs), namely EfficientNetB0 and DenseNet121. These models are utilized to extract deep features from images depicting corn plants. The research aims to compare the performance of the proposed model with other pre-trained CNN architectures, specifically ResNet152 and InceptionV3, known for their larger parameter sizes and computational

demands.

The experimental results demonstrate the superiority of the proposed model, achieving an impressive classification accuracy of 98.56

The architecture of the proposed CNN model is delineated, comprising two branches, each equipped with a preprocessing function, a feature extractor, average pooling, and a fully connected layer. This design facilitates the extraction of dis- criminative features from input images, contributing to the model's exceptional performance in disease classification.

The research contributes to the advancement of plant pathol- ogy and agricultural technology by introducing an efficient and accurate approach for disease diagnosis. By leveraging state- of-the-art deep learning techniques and carefully selecting pre- trained CNN architectures, the proposed model demonstrates its potential as a valuable tool for plant disease management and crop protection efforts.

Moreover, the findings underscore the importance of model selection and architecture design in optimizing performance for specific tasks. The utilization of EfficientNetB0 and DenseNet121 showcases the significance of considering model characteristics such as parameter efficiency and feature extrac- tion capabilities in achieving superior results.

Overall, the study provides valuable insights into the ap- plication of deep learning in agricultural research and under- scores the potential of advanced computational techniques in addressing critical challenges in plant health monitoring and disease control.[7].

Plant diseases and pests pose formidable challenges to agri- culture, exerting a substantial impact on crop yield and quality. Effective identification and management of these issues are imperative to ensure food security and sustainable agricultural practices. In recent years, digital image processing and deep learning have emerged as powerful tools for addressing the complexities associated with plant disease and pest identifi- cation, offering promising avenues for improved agricultural practices and crop protection.

The proposed method represents a comprehensive approach that integrates various stages, including data preprocessing, feature fusion, feature sharing, and disease detection, to en- hance the accuracy and efficiency of plant disease and pest identification systems. Data preprocessing plays a pivotal role in optimizing image quality, with adequate sunlight conditions yielding the best results. In contrast, capturing images in cloudy weather can increase the complexity of preprocessing tasks and diminish the recognition efficacy.

The utilization of deep learning techniques facilitates the extraction of intricate patterns and features from plant images, enabling the identification and classification of diseases and pests with high precision. Feature fusion techniques amal- gamate information from multiple sources, enhancing the discriminative power of the model and improving classification accuracy. Furthermore, feature sharing mechanisms enable the efficient utilization of shared knowledge across different disease and pest categories, optimizing model performance and reducing computational overhead.

Disease detection is a critical component of the proposed method, allowing for the timely and accurate identification of plant health issues. By leveraging advanced machine learning algorithms, the system can differentiate between healthy plants and those affected by diseases or pests, enabling prompt intervention and mitigation measures. Moreover, the proposed method incorporates feedback mechanisms to iteratively refine the model's performance, ensuring continuous improvement in disease detection accuracy and reliability.

Despite its efficacy, the proposed method faces certain challenges, particularly in image preprocessing under adverse weather conditions. Cloudy weather can introduce variability and noise into the images, necessitating sophisticated prepro- cessing techniques to enhance image quality and facilitate accurate disease detection. Additionally, scalability and com- putational resource requirements may pose constraints on the deployment of the method in large-scale agricultural settings. In conclusion, the proposed method represents a promis- ing approach for addressing the challenges of plant disease and pest identification in agriculture. By leveraging digital image processing and deep learning techniques, the method offers enhanced accuracy and efficiency in disease detection and management. However, further research and development efforts are needed to overcome challenges related to image preprocessing, scalability, and resource constraints, ultimately realizing the full potential of digital technologies in revo- lutionizing agricultural practices and ensuring global food
security.[8].

This research introduces "PiTLiD," a pioneering approach aimed at bolstering the accuracy of plant disease recognition through the synergistic application of transfer learning and deep convolutional neural networks (CNNs). Emphasizing the paramount importance of training models on large-scale, real- world datasets characterized by complex backgrounds, the study addresses inherent challenges in plant disease recogni- tion with a comprehensive framework.

Central to the research's innovation is its systematic analysis of the obstacles encountered in plant disease recognition and the proposal of a holistic solution. By leveraging transfer learning techniques and deep CNN architectures, PiTLiD demonstrates notable advancements in disease recognition accuracy, setting a new standard in intelligent agriculture analysis.

A significant contribution of this work lies in the devel- opment of a substantial plant disease dataset, denoted as PDD271, meticulously collected under authentic real-world conditions. This dataset fills a critical gap in the field by pro- viding researchers with a comprehensive resource for training and testing plant disease recognition algorithms. By incorpo- rating diverse scenarios and backgrounds, PDD271 facilitates more robust and generalized model training, ultimately en- hancing the performance of plant disease recognition systems. Moreover, beyond its immediate applications in plant dis- ease recognition, this research holds broader implications for the advancement of intelligent agriculture analysis and understanding. By leveraging cutting-edge techniques in image
processing and computer vision, PiTLiD not only improves the accuracy of disease recognition but also fosters progress in the broader fields of agricultural technology and automated farming systems.

In summary, the introduction of PiTLiD represents a signif- icant leap forward in the realm of plant disease recognition, offering a novel approach that addresses critical challenges and leverages state-of-the-art methodologies. Through the de- velopment of the PDD271 dataset and the systematic analysis of plant disease recognition challenges, this research not only enhances the accuracy of disease detection but also provides invaluable resources for advancing intelligent agriculture anal- ysis and understanding, paving the way for transformative developments in agricultural technology and food security.[9].

METHODOLOGY

overfitting by randomly setting a fraction of input units tozero during training.

3. Full Model: - The full CNN model is constructed by connecting the input layer to the feature extractor and ma- nipulation detection network. - The input layer is defined with the specified input size (224x224x3), matching the dimensions of the input images. - The manipulation detection network

receives the features that the feature extractor has collected and classifies them immediately. - The resulting model is compiled and returned for training and evaluation.

Overall, this architecture approach simplifies the CNN model by directly connecting the feature extractor to the classification layer, facilitating the detection and classificationof diseases.

Overview

The methodology for implementing the CNN model in- volves thorough data preprocessing, model architecture de- sign, training procedures, hyperparameter optimization, and potential modifications or enhancements. Initially, the dataset, comprising 39 types of diseases of leafs, and images for all those diseases undergoes Error Level Analysis (ELA) and standardization to prepare it for input into the model. The CNN architecture comprises two main sub-networks: one for feature extraction and another for disease detection, facilitating the identification of class of disease.The binary cross-entropy loss function and Adam optimizer are used to train the model once the dataset has been divided into validation,training and testing sets. To maximize performance of model, hyperparameters like batch size,learning rate and epochs are adjusted. Modifications or enhancements to the original model may be considered to improve its efficacy, including adjustments to the architecture, loss functions, or preprocessing steps. Overall, this method- ology ensures a robust and effective approach to detect the disease of plant leaf with the CNN model.

Deep Learning Approaches

1) ***CNN*** *: .*

1. Feature Extractor: - The feature extractor is built as asequential model with many convolutional layers and max-

Dataset

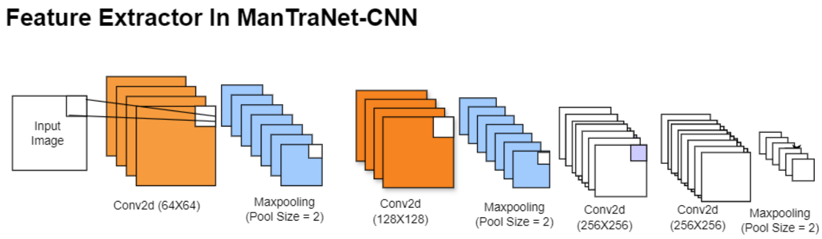

Fig. 2. (a) Architecture of CNN

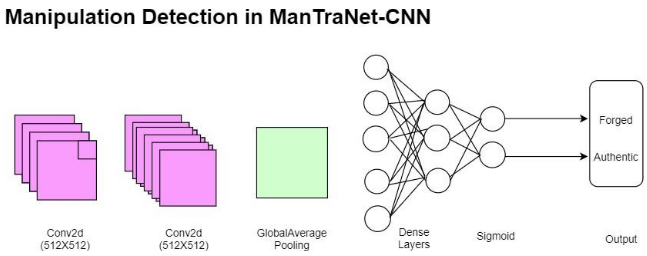

Fig. 3. (b) Architecture of InceptionV3

EXPERIMENTAL SETUP

pooling layers in order of precedence. - It starts with a convolutional layer that has 32 filters with ReLU activation and 3x3 kernel sizes. - Additional convolutional layers with progressively more filters (128 and 256) are included in the subsequent layers. - In order to efficiently extract dominating features and decrease spatial dimensions, max-pooling layers are inserted between convolutional layers.

Classification Layer: The classification is handled by the dense layers. The convolutional and pooling layers that extract features from the input images, the dense layers serve as the fully connected layers that perform the final classification task. The dense layers receive the flattened output from the previous layers and apply weights to predict the class prob- abilities.Additionally, dropout layers are included to prevent

The PlantVillage dataset is created to bring efficient solutions in order to detect 39 dif ferent plant diseases. It contains 61,486 images of plant leaves and backgrounds. It was created with six different augmentation techniques for creating more diverse datasets with different background conditions. The augmentations used in this process were scaling, rotation, noise injection, gamma correction, image flipping, and PCA color aug mentation.

Dataset Name : Plant Village DataetTotal Count Of Images : 60000 Total Number of Classes : 39

Classes : Apple Apple scab,Apple Black rot,Apple Cedar apple rust,Apple healthy,Background without leaves,Blueberry healthy,Cherry Powdery mildew,Cherry healthy,Corn Cercospora leaf spot Gray leaf spot,Corn Common rust,Corn Northern Leaf Blight,Corn healthy,Grape Black rot,Grape Esca (Black Measles), Grape Leaf blight (Isariopsis Leaf Spot),Grape healthy,Orange Haunglongbing (Citrus greening),Peach Bacterial spot,Peach healthy,Pepper bell Bacterial spot,Pepper bell healthy,Potato Early blight,Potato Late blight,Potato healthy,Raspberry healthy ,Soybean healthy,Squash Powdery mildew,Strawberry Leaf scorch,Strawberry healthy,Tomato Bacterial spot,Tomato Early blight,Tomato Late blight,Tomato Leaf Mold,Tomato Septoria leaf spot,Tomato Target Spot,Tomato Tomato Yellow Leaf Curl Virus,Tomato Tomato mosaic virus,Tomatohealthy,Tomato spider

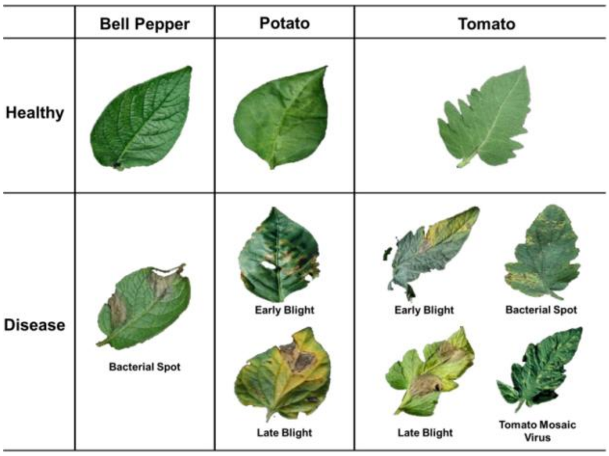

Fig. 4. Dataset consisting healthy and deiseased images

Dataset Features

1. The PlantVillage dataset used in this project includes high-quality images of plant leaves, each up to 1MB, across 39 classes representing various plant diseases.
2. Python Programming Language: Python is used for implementing the experimental setup, including data preprocessing, model construction, and evaluation.
3. Flutter : Flutter is used for User Interface Design.Flutter allows for creating natively compiled applications for mobile, web, and desktop from a single codebase. Its rich set of widgets and flexible UI framework enabled us to build a responsive and visually appealing interface quickly.
4. Hardware Infrastructure: The experimental setup may require access to computational resources, such as CPUs or GPUs, to facilitate model training and testing effi- ciently.
5. Data Visualization Libraries: Libraries like Matplotlib and Seaborn may be used for visualizing experimental results, including accuracy metrics, confusion matrices, and precision-recall curves.

D. Implications and Use Cases

By providing a cost-effective and accessible solution for timely and accurate plant disease detection, the project en- hances agricultural productivity and reduces crop losses. Farm- ers can use the mobile application to scan leaves in real- time, receiving instant disease diagnoses and enabling prompt action. This promotes sustainable farming practices through targeted pesticide use and contributes to data-driven decision- making in agriculture. Additionally, agricultural extension workers can leverage the app to assist multiple farmers, while research institutions can utilize the dataset and model for studying plant diseases and developing new treatments. Overall, this project supports increased yield, cost savings, and environmental sustainability in agriculture.

E. Performance Evaluation

Accuracy: The classifier's total correctness across allclasses is gauged using a statistic called accuracy.
Images are standardized to 224x224 pixels with RGB
channels and undergo preprocessing such as resizing andnormalization.

Accuracy

$$= \frac{TP + TN}{TP + TN + FP + FN} \qquad (1)$$

The dataset is divided into training, validation, and testsets for effective model training and evaluation.
Image augmentations, including rotations, flips, zoom-
Precision: A statistic called precision tells us how many
right positive predictions out of all the positive predictions aclassifier generates.
ing, and brightness adjustments, enhance the dataset'sdiversity and robustness. Each image has associated

$$\text{Precision} = \frac{TP}{TP + FP} \qquad (2)$$

metadata, such as unique file names and class labels, with target variables represented as one-hot encodedvectors.
This comprehensive dataset supports the development of
3) Recall: Measured against all actual positive occurrences in the dataset, the recall measure (sometimes called sensitivity or true positive rate, or TPR)) assesses the accuracy of positivepredictions.
a CNN model for accurate plant disease classification
and detection, ensuring strong generalization to new,

$$\text{Recall} = \frac{TP}{TP + FN} \qquad (3)$$

unseen data.

C. Tools and Technology

1) TensorFlow and Keras: The experimental setup leverages
4) F1 Score: One statistic that strikes a compromise be- tween recall and accuracy is the F1 score, which is calculated by taking the harmonic mean of the two.
TensorFlow and Keras, deep learning frameworks, formodel development and training.

$$\text{F1 Score} = 2 \quad \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad \times$$

We have investigated a suggested approach for detecting picture forgeries, and it shows good F1-score, recall, preci- sion metrics for both real and fake photos. Precision, recall, and F1-score for forged photos are 0.91, 0.95, and 0.93, respectively,promote efficient identification with minimal false negatives and positives. Comparably, the valid photographs have an F1-score- 0.97, a precision- 0.98, and a recall- 0.97., proving to be quite accurate in identifying genuine photos.The weighted-average, macro-average, F1-scores indicate that the model's accuracy is 0.96, at 0.95 and 0.96. With interesting implications for a range of applications in picture forensics and media integrity verification, our results demonstrate the robustness and dependability of the suggested technique in detecting image forgeries.

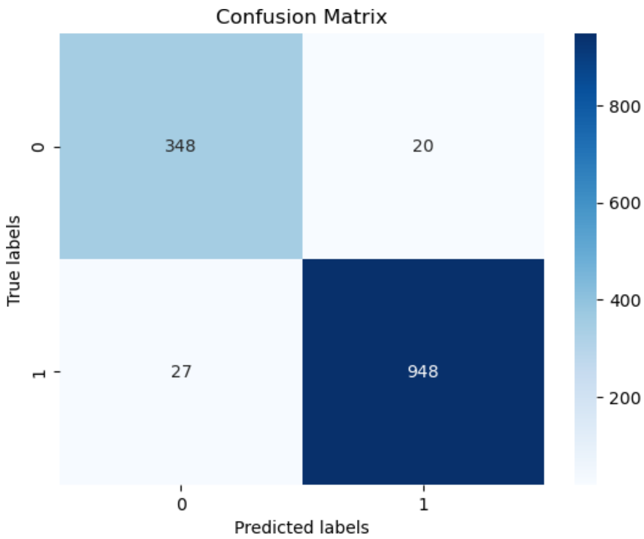

Fig. 5. Performance of CNN models

RESULTS

Fig. 6. Original

Fig. 7. Forged

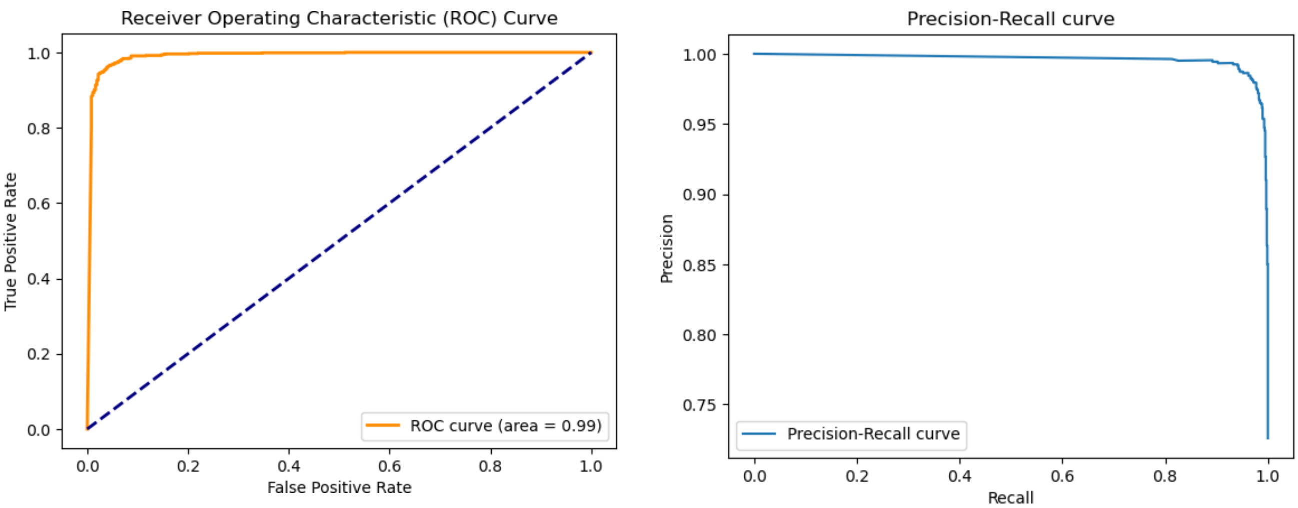

Fig. 8. Performance of CNN models

CONCLUSION

The successful attainment of high accuracy in plant disease detection through deep learning methodologies, particularly Convolutional Neural Networks (CNNs), heralds promising prospects for real-world implementation in smart farming practices. This project underscores the pivotal significance of CNNs in capturing disease-specific attributes from leaf images, emphasizing the critical role of accurate diagnosis in ensuring food security and bolstering agricultural productivity. By advancing plant phenomics and providing a crucial tool for efficient and cost-effective disease diagnosis, this project contributes significantly to the sustainability and productiv- ity of the agricultural landscape. Its findings highlight the transformative potential of deep learning in revolutionizing agricultural practices, showcasing the importance of leveraging advanced technologies for tackling pressing challenges in crop management. Ultimately, the project's outcomes serve as a beacon for future research endeavors aimed at enhancing agricultural sustainability and global food security throughinnovative technological solutions.

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